Brain Tumour Classification through MRI Images Using Deep Learning

1.Introduction

- The occurrence of brain tumor patients in India is steadily rising, more and more number of cases are reported each year in India across various age groups.

2. Setting Up Local Storage for Dataset

2.1 Giving Access To Google Drive

```
from google.colab import drive
drive.mount('/content/gdrive/')

Mounted at /content/gdrive/
```

2.2 Checking OS Version and Details

```
print("OS Version & Details: ")
!lsb_release -a

OS Version & Details:
No LSB modules are available.
Distributor ID:	Ubuntu
Description:	Ubuntu 22.04.4 LTS
Release:	22.04
Codename:	jammy
```

3. Importing Required Libraries

```
import sys
import os
import math

import numpy as np
import pandas as pd

from matplotlib import pyplot as plt
from matplotlib import rcParams
rcParams['figure.dpi'] = 300
%matplotlib inline
import seaborn as sns
import missingno as msno
import plotly.express as px
import plotly.graph_objects as go
```

```
from plotly.subplots import make_subplots

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import *
from tensorflow.keras.optimizers import *
from tensorflow.keras.applications import InceptionV3
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import *

from PIL import Image, ImageEnhance
from tensorflow.keras.preprocessing.image import *

print(f'Tensorflow Version: {tf.__version__}.')
```

```
Tensorflow Version: 2.18.0.
```

4. Setting Up the Environment

```
gpu_device_location = tpu_device_location = cpu_device_location = None

if os.environ['COLAB_GPU'] == '1':
    print("Allocated GPU Runtime Details:")
    !nvidia-smi
    print()
    try:
        import pynvml
        pynvml.nvmlInit()
        handle = pynvml.nvmlDeviceGetHandleByIndex(0)
        gpu_device_name = pynvml.nvmlDeviceGetName(handle)

        if gpu_device_name not in {b'Tesla T4', b'Tesla P4', b'Tesla
P100-PCIE-16GB'}:
            raise Exception("Unfortunately this instance does not have
a T4, P4 or P100 GPU.\nSometimes Colab allocates a Tesla K80 instead
of a T4, P4 or P100.\nIf you get Tesla K80 then you can factory reset
your runtime to get another GPUs.")
    except Exception as hardware_exception:
        print(hardware_exception, end = '\n\n')
    gpu_device_location = tf.test.gpu_device_name()
    print(f"{gpu_device_name} is allocated successfully at location:
{gpu_device_location}")
elif 'COLAB_TPU_ADDR' in os.environ:
    tpu_device_location = f"grpc://{os.environ['COLAB_TPU_ADDR']}"
    print(f"TPU is allocated successfully at location:
{tpu_device_location}.")
    resolver =
tf.distribute.cluster_resolver.TPUClusterResolver(tpu_location)
    tf.config.experimental_connect_to_cluster(resolver)
```

```
    tf.tpu.experimental.initialize_tpu_system(resolver)
    tpu_strategy = tf.distribute.TPUStrategy()
else:
    cpu_device_location = "/cpu:0"
    print("GPUs and TPUs are not allocated successfully, hence runtime
fallbacked to CPU.")
```

```
Allocated GPU Runtime Details:
Thu Jul 24 12:47:14 2025
+-----------------------------------------------------------------------
---------------------+
| NVIDIA-SMI 550.54.15              Driver Version: 550.54.15
CUDA Version: 12.4     |
|-----------------------------------------+------------------------
+----------------------+
| GPU  Name                 Persistence-M | Bus-Id          Disp.A |
Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |           Memory-Usage |
GPU-Util  Compute M. |
|                                         |                        |
MIG M. |
|
=========================================+========================+===
===================|
|   0  Tesla T4                       Off |   00000000:00:04.0 Off |
0 |
| N/A   59C    P0             29W /   70W |     102MiB /  15360MiB |
0%      Default |
|                                         |                        |
N/A |
+-----------------------------------------+------------------------
+----------------------+


+-----------------------------------------------------------------------
---------------------+
| Processes:
|
|  GPU   GI   CI        PID   Type   Process name
GPU Memory |
|        ID   ID
Usage      |
|
=======================================================================
===================|
+-----------------------------------------------------------------------
---------------------+

Unfortunately this instance does not have a T4, P4 or P100 GPU.
Sometimes Colab allocates a Tesla K80 instead of a T4, P4 or P100.
```

```
If you get Tesla K80 then you can factory reset your runtime to get
another GPUs.

Tesla T4 is allocated successfully at location: /device:GPU:0
```

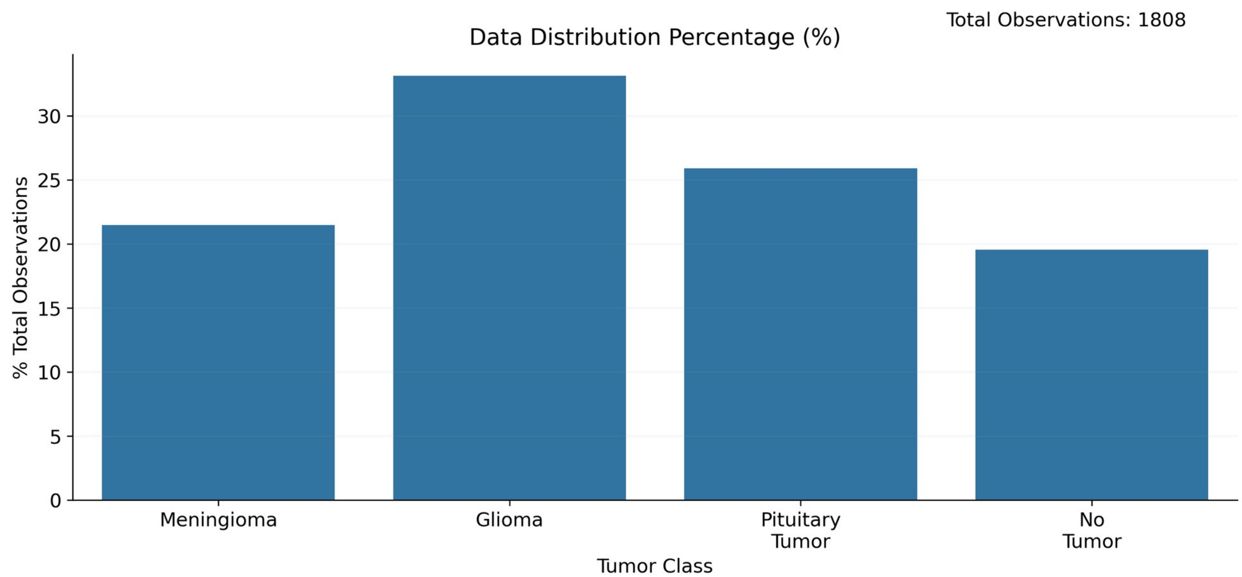
5. Data Preprocessing and Exploratory Data Analysis

```python
import os
import pandas as pd

# Define folder paths directly
meningioma_path = "/content/gdrive/MyDrive/Brain
Tumour/train/meningioma"
glioma_path = "/content/gdrive/MyDrive/Brain Tumour/train/glioma"
pituitary_path = "/content/gdrive/MyDrive/Brain
Tumour/train/pituitary"
no_tumor_path = "/content/gdrive/MyDrive/Brain Tumour/train/no_tumor"

# Count images in each folder
data_distribution_count = pd.Series({
    'meningioma': len(os.listdir(meningioma_path)),
    'glioma': len(os.listdir(glioma_path)),
    'pituitary_tumor': len(os.listdir(pituitary_path)),
    'no_tumor': len(os.listdir(no_tumor_path))
})

# Show the counts
print(data_distribution_count)
```

```
meningioma         388
glioma             599
pituitary_tumor    468
no_tumor           353
dtype: int64
```

5.1 Data Distribution Visualization

```python
fig, axis = plt.subplots(figsize = (13, 5))
axis.grid(True, alpha = 0.1)
axis.set_title("Data Distribution Percentage (%)", fontsize = 14)
sns.barplot(x = ['\n'.join(curr_index.strip().split('_')).title() for
curr_index in data_distribution_count.index],
            y = 100 * (data_distribution_count /
data_distribution_count.sum()), ax = axis)
axis.set_xlabel("Tumor Class", fontsize = 12)
axis.set_ylabel("% Total Observations", fontsize = 12)
axis.tick_params(which = 'major', labelsize = 12)
axis.text(2.5, 37, f'Total Observations:
{data_distribution_count.sum()}', fontdict = dict(size = 12))
sns.despine()
```



5.2 Visualisation of Brain MRI Dataset

Dataset Source: https://figshare.com/articles/dataset/brain_tumor_dataset/1512427

Source Code for Conversion of `.mat` file to `.jpg`: Google Colab Notebook Link

Final Dataset Link: https://drive.google.com/drive/folders/11QIC82FBdAyq0PUwLVNd22i-oq6lcat1?usp=sharing

```
import matplotlib.pyplot as plt
import cv2
import os

# Set the path to each class folder
image_paths = {
    "Meningioma": "/content/gdrive/MyDrive/Brain 
Tumour/train/meningioma",
    "Glioma": "/content/gdrive/MyDrive/Brain Tumour/train/glioma",
    "Pituitary Tumor": "/content/gdrive/MyDrive/Brain 
Tumour/train/pituitary"
}

# Create subplots - 1 row, 3 columns
fig, axes = plt.subplots(1, 3, figsize=(15, 5))
fig.suptitle("Brain Tumor MRI Images (T2w)", fontsize=16, 
fontweight="bold")

# Loop through classes and display one image from each
for ax, (label, path) in zip(axes, image_paths.items()):
    image_file = os.listdir(path)[0]  # Just take the first image
    img = cv2.imread(os.path.join(path, image_file))
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
```

```
    ax.imshow(img)
    ax.set_title(label)
    ax.axis('off')

plt.tight_layout()
plt.show()
```

6. Development of Training, Validation & Testing Dataset

```
import os

# Define base path
BASE_PATH = "/content/gdrive/MyDrive/Brain Tumour/train"

# Define tumor class folder names
TUMOR_CLASS = ["glioma", "meningioma", "pituitary", "no_tumor"]

# Create image data paths
IMAGE_DATA_PATHS = [os.path.join(BASE_PATH, cls) for cls in
TUMOR_CLASS]

# Now extract all (image_path, class_label) pairs
image_data_paths = [
    (os.path.join(curr_path, filename), tumor_name)
    for curr_path, tumor_name in zip(IMAGE_DATA_PATHS, TUMOR_CLASS)
    if os.path.isdir(curr_path)
    for filename in os.listdir(curr_path)
]

import pandas as pd
df = pd.DataFrame(image_data_paths, columns=["image_path", "label"])
df.head()
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 1808,\n  \"fields\":
[\n    {\n      \"column\": \"image_path\",\n      \"properties\": {\n
\"dtype\": \"string\",\n        \"num_unique_values\": 1808,\n
\"samples\": [\n          \"/content/gdrive/MyDrive/Brain
```

```
Tumour/train/no_tumor/Tr-
no_0271_jpg.rf.3a807ec442e7776e4d04f2ffd1c5fbb3.jpg\",\n
\"/content/gdrive/MyDrive/Brain Tumour/train/glioma/Tr-
gl_0076_jpg.rf.58ab815342a7fd013913e585834779f1.jpg\",\n
\"/content/gdrive/MyDrive/Brain Tumour/train/meningioma/Tr-
me_0199_jpg.rf.d16239216a1cff51b2104a9f1149e92d.jpg\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"label\",\n      \"properties\": {\
n        \"dtype\": \"category\",\n        \"num_unique_values\": 4,\n
\"samples\": [\n          \"meningioma\",\n          \"no_tumor\",\n
\"glioma\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df"}
```


```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1808 entries, 0 to 1807
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   image_path  1808 non-null   object
 1   label       1808 non-null   object
dtypes: object(2)
memory usage: 28.4+ KB
```

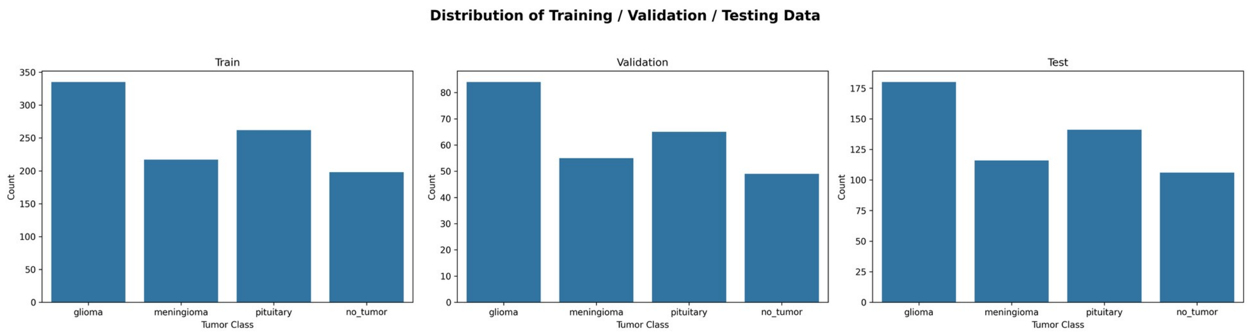
```python
import pandas as pd
from sklearn.model_selection import train_test_split

# Step 1: Convert to DataFrame
df = pd.DataFrame(image_data_paths, columns=["image_path",
"tumor_class"])

# Step 2: First split — train + val vs test (70-30)
intermediate_train_data, test_data = train_test_split(
    df,
    train_size=0.70,
    random_state=42,
    stratify=df["tumor_class"]
)

# Step 3: Split train into train + val (80-20 of the 70%)
train_data, validation_data = train_test_split(
    intermediate_train_data,
    train_size=0.80,
    random_state=42,
    stratify=intermediate_train_data["tumor_class"]
)
```

6.1 Training, Validation and Testing Dataset Data Distribution Visualization

```
# --- Imports ---
import os
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

# --- Mount Google Drive ---
from google.colab import drive
drive.mount('/content/drive')

# --- Tumor Classes ---
TUMOR_CLASS = ['glioma', 'meningioma', 'pituitary', 'no_tumor']

# --- Dataset Root ---
DATA_ROOT = "/content/drive/MyDrive/Brain Tumour"

# --- Folder paths for each class under train ---
IMAGE_DATA_PATHS = [os.path.join(DATA_ROOT, 'train', cls) for cls in
TUMOR_CLASS]

# --- Load image paths into dataframe ---
image_data_paths = []

for curr_path, tumor_name in zip(IMAGE_DATA_PATHS, TUMOR_CLASS):
    if os.path.exists(curr_path) and os.path.isdir(curr_path):
        for filename in os.listdir(curr_path):
            if filename.lower().endswith(('.jpg', '.jpeg', '.png')):
                full_path = os.path.join(curr_path, filename)
                image_data_paths.append((full_path, tumor_name))

print(f"□ Total images found: {len(image_data_paths)}")

# --- Create dataframe ---
image_df = pd.DataFrame(image_data_paths, columns=["image_path",
"tumor_class"])

# --- Sanity check ---
print(image_df.head())
print(image_df['tumor_class'].value_counts())

# --- Train/Val/Test Split ---
intermediate_train_data, test_data = train_test_split(
    image_df,
    train_size=0.70,
    stratify=image_df['tumor_class'],
    random_state=42
```

```
)

train_data, validation_data = train_test_split(
    intermediate_train_data,
    train_size=0.80,
    stratify=intermediate_train_data['tumor_class'],
    random_state=42
)

print("Train size:", len(train_data))
print("Validation size:", len(validation_data))
print("Test size:", len(test_data))

# --- Plot Class Distribution ---
fig, axes = plt.subplots(ncols=3, figsize=(20, 5))
fig.suptitle("Distribution of Training / Validation / Testing Data",
fontsize=16, weight='bold', y=1.05)

sns.countplot(x=train_data.tumor_class, order=TUMOR_CLASS, ax=axes[0])
axes[0].set_title("Train")
axes[0].set_ylabel("Count")
axes[0].set_xlabel("Tumor Class")

sns.countplot(x=validation_data.tumor_class, order=TUMOR_CLASS,
ax=axes[1])
axes[1].set_title("Validation")
axes[1].set_ylabel("Count")
axes[1].set_xlabel("Tumor Class")

sns.countplot(x=test_data.tumor_class, order=TUMOR_CLASS, ax=axes[2])
axes[2].set_title("Test")
axes[2].set_ylabel("Count")
axes[2].set_xlabel("Tumor Class")

plt.tight_layout()
plt.show()

Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
□ Total images found: 1808
                                          image_path tumor_class
0  /content/drive/MyDrive/Brain Tumour/train/glio...      glioma
1  /content/drive/MyDrive/Brain Tumour/train/glio...      glioma
2  /content/drive/MyDrive/Brain Tumour/train/glio...      glioma
3  /content/drive/MyDrive/Brain Tumour/train/glio...      glioma
4  /content/drive/MyDrive/Brain Tumour/train/glio...      glioma
tumor_class
glioma        599
pituitary     468
meningioma    388
```

```
no_tumor      353
Name: count, dtype: int64
Train size: 1012
Validation size: 253
Test size: 543
```



7. Data/Image Augmentation

- Image augmentation is usually used to increase the image dataset and also to make the network more robust against translation invariance. Image augmentation is defined as creating duplicates of the original image datasets by flipping, rotating, zooming, and adjusting brightness.

- We will use data/image augmentation using `ImageDataGenerator` class to train the model on different types of combinations formed by rotation, flipping, changing the brightness etc of an image so as to increase our model accuracy.

```
image_size = 128
batch_size = 32

image_datagen_kwargs = dict(rescale = 1 / 255,
                            rotation_range = 15,
                            width_shift_range = 0.1,
                            zoom_range = 0.01,
                            shear_range = 0.01,
                            brightness_range = [0.3, 1.5],
                            horizontal_flip = True,
                            vertical_flip = True)

train_image_datagen = ImageDataGenerator(**image_datagen_kwargs)
validation_image_datagen = ImageDataGenerator(**image_datagen_kwargs)
test_image_datagen = ImageDataGenerator(**image_datagen_kwargs)

train_dataset = train_image_datagen.flow_from_dataframe(train_data,
                                                        x_col =
'image_path',
                                                        y_col =
'tumor_class',
                                                        seed = 42,
```

```
                                                        batch_size =
batch_size,
                                                        target_size =
(image_size, image_size),
                                                        color_mode =
'rgb')
validation_dataset =
validation_image_datagen.flow_from_dataframe(validation_data,

x_col = 'image_path',

y_col = 'tumor_class',
                                                                  seed
= 42,

batch_size = batch_size,

target_size = (image_size, image_size),

color_mode = 'rgb')
test_dataset = test_image_datagen.flow_from_dataframe(test_data,
                                                      x_col =
'image_path',
                                                      y_col =
'tumor_class',
                                                      seed = 42,
                                                      batch_size =
batch_size,
                                                      target_size =
(image_size, image_size),
                                                      color_mode =
'rgb')
```

```
Found 1012 validated image filenames belonging to 4 classes.
Found 253 validated image filenames belonging to 4 classes.
Found 543 validated image filenames belonging to 4 classes.
```

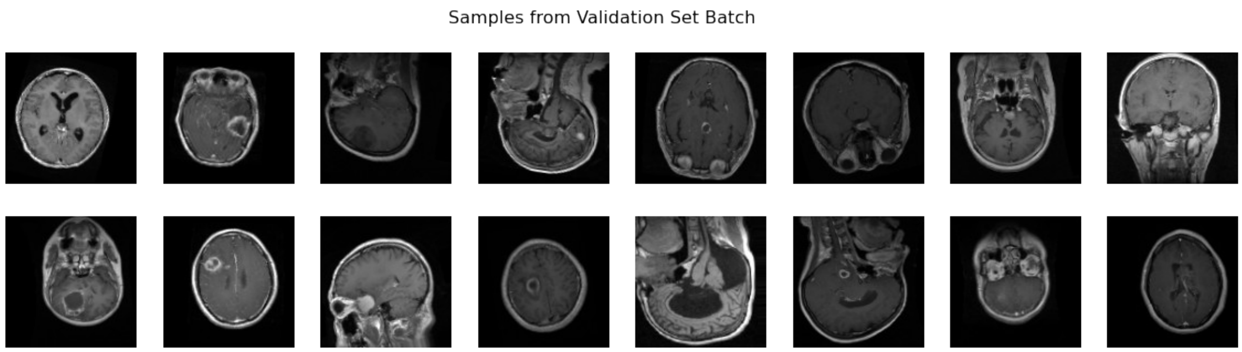
```
print("Information about Training Dataset:")
print(train_dataset.class_indices)
print(train_dataset.image_shape, end = '\n\n')

print("Information about Validation Dataset:")
print(validation_dataset.class_indices)
print(validation_dataset.image_shape, end = '\n\n')

print("Information about Testing Dataset:")
print(test_dataset.class_indices)
print(test_dataset.image_shape)
```

```
Information about Training Dataset:
{'glioma': 0, 'meningioma': 1, 'no_tumor': 2, 'pituitary': 3}
```

```
(128, 128, 3)

Information about Validation Dataset:
{'glioma': 0, 'meningioma': 1, 'no_tumor': 2, 'pituitary': 3}
(128, 128, 3)

Information about Testing Dataset:
{'glioma': 0, 'meningioma': 1, 'no_tumor': 2, 'pituitary': 3}
(128, 128, 3)
```

7.2 Validation Data Images Glimpse

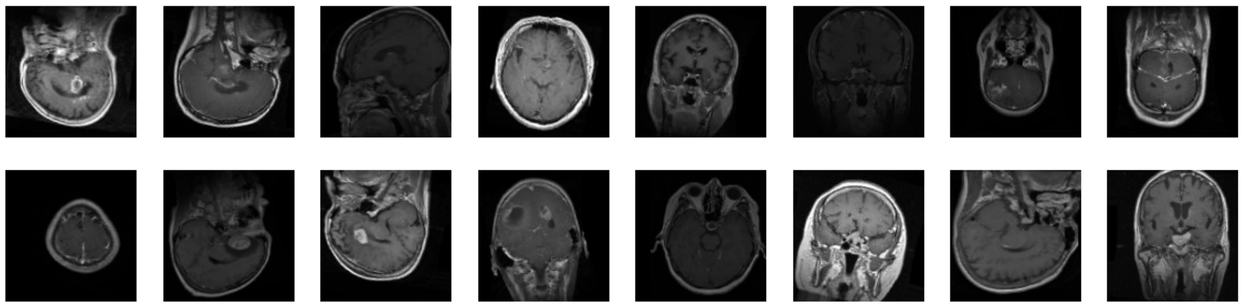
```
fig, axes = plt.subplots(nrows = 2, ncols = 8, figsize = (20, 5))
fig.suptitle("Samples from Validation Set Batch", fontsize = 16,
fontdict = dict(weight = 'bold'))
for curr_axis, curr_image in zip(axes.flatten(), validation_dataset[0]
[0][:16]):
    curr_axis.imshow(tf.squeeze(curr_image), cmap = 'gray')
    curr_axis.axis(False)
```



7.3 Testing Data Images Glimpse

```
fig, axes = plt.subplots(nrows = 2, ncols = 8, figsize = (20, 5))
fig.suptitle("Samples from Testing Set Batch", fontsize = 16, fontdict
= dict(weight = 'bold'))
for curr_axis, curr_image in zip(axes.flatten(), test_dataset[0][0]
[:16]):
    curr_axis.imshow(tf.squeeze(curr_image), cmap = 'gray')
    curr_axis.axis(False)
```

Samples from Testing Set Batch



8. Model Development

```
early_stopping = EarlyStopping(monitor = 'val_accuracy', patience =
10)

ROOT_CHECKPOINT_DIR_PATH = os.path.join(ROOT_DIR, "Model-Checkpoints")
MLP_CHECKPOINT_DIR_PATH = os.path.join(ROOT_CHECKPOINT_DIR_PATH,
"Multi-Layer-Perceptron")
ALEXNET_CHECKPOINT_DIR_PATH = os.path.join(ROOT_CHECKPOINT_DIR_PATH,
"AlexNet-CNN")
INCEPTIONV3_CHECKPOINT_DIR_PATH =
os.path.join(ROOT_CHECKPOINT_DIR_PATH, "InceptionV3")
assert os.path.isdir(ROOT_CHECKPOINT_DIR_PATH) and
os.path.isdir(MLP_CHECKPOINT_DIR_PATH) and
os.path.isdir(ALEXNET_CHECKPOINT_DIR_PATH) and
os.path.isdir(INCEPTIONV3_CHECKPOINT_DIR_PATH)

mlp_cp_callback = ModelCheckpoint(MLP_CHECKPOINT_DIR_PATH,
                                  monitor = 'val_accuracy',
                                  verbose = 1,
                                  save_weights_only = True,
                                  save_freq =  'epoch')

alexnet_cp_callback = ModelCheckpoint(ALEXNET_CHECKPOINT_DIR_PATH,
                                      monitor = 'val_accuracy',
                                      verbose = 1,
                                      save_weights_only = True,
                                      save_freq = 'epoch')

inceptionv3_cp_callback =
ModelCheckpoint(INCEPTIONV3_CHECKPOINT_DIR_PATH,
                                          monitor = 'val_accuracy',
                                          verbose = 1,
                                          save_weights_only = True,
                                          save_freq = 'epoch')

def training_process_viz(training_stats: pd.DataFrame, **plot_kwargs)
-> None:
    fig, axes = plt.subplots(ncols = 2, figsize = (15, 5))
```

```
    fig.suptitle(plot_kwargs['plot_title'], fontsize = 16, fontdict =
dict(weight = 'bold'), y = 1.08)
    for curr_axis, col_name in zip(axes, ['accuracy', 'loss']):
        curr_axis.grid(True, alpha = 0.3)
        curr_axis.set_title(f"Model {col_name}".title(), fontsize =
14)
        sns.lineplot(x = range(1, 1 + training_stats.shape[0]), y =
training_stats[col_name], color = 'blue', ax = curr_axis)
        sns.lineplot(x = range(1, 1 + training_stats.shape[0]), y =
training_stats[f"val_{col_name}"], color = 'red', ax = curr_axis)
        curr_axis.set_xlabel("Epochs", fontsize = 12)
        curr_axis.set_ylabel(col_name.title(), fontsize = 12)
        curr_axis.tick_params(which = 'major', labelsize = 12)
        curr_axis.legend([col_name.title(), f"validation
{col_name}".title()], title = col_name.title())
    fig.tight_layout()
    sns.despine()

def confusion_matrix_viz(model, test_dataset, **plot_kwargs) -> None:
    assert isinstance(model, Sequential)
    model_preds = [np.argmax(curr_row) for curr_row in
model.predict(test_dataset)]
    fig, axis = plt.subplots(figsize = (8, 6))
    class_names = ['Glioma', 'Meningioma', 'No-Tumor', 'Pituitary\
nTumor']
    sns.heatmap(confusion_matrix(test_dataset.classes, model_preds),
annot = True, cmap = plt.cm.Reds, ax = axis)
    axis.set_title(plot_kwargs['plot_title'], fontsize = 14)
    axis.tick_params(which = 'major', labelsize = 12)
    axis.set_xlabel("Pedicted Class", fontsize = 12)
    axis.set_ylabel("Actual Class", fontsize = 12)
    axis.set_xticklabels(class_names, fontdict = dict(fontsize = 12))
    axis.set_yticklabels(class_names, fontdict = dict(fontsize = 12))
    fig.tight_layout()
    sns.despine()

def generate_report(*models, test_dataset, row_indexes) ->
pd.DataFrame:
    assert len(models)
    report_df = pd.DataFrame(columns = ['MAE', 'MSE', 'RMSE', 'Loss',
'Accuracy', 'F1-Score'])
    y_hat = test_dataset.classes # y_hat = ground_truth
    for curr_index, curr_model in enumerate(models):
        assert isinstance(curr_model, Sequential)
        curr_model_loss, curr_model_accuracy =
curr_model.evaluate(test_dataset)
        y_preds = [np.argmax(curr_preds) for curr_preds in
curr_model.predict(test_dataset)]
        report_df.loc[curr_index] = [mean_absolute_error(y_hat,
y_preds), mean_squared_error(y_hat, y_preds),
```

```
mean_squared_error(y_hat, y_preds, squared = False), curr_model_loss,
curr_model_accuracy, f1_score(y_hat, y_preds, average = "micro")]
    report_df.index = row_indexes
    return report_df
```

8.1 Multi-Layer Perceptron

8.1.1 Development of Multi-Layer Perceptron Model

```
mlp_model = Sequential()
mlp_model.add(Flatten(input_shape = (image_size, image_size, 3), name
= 'Flatten-Layer'))
mlp_model.add(Dense(2048, activation = 'relu', name = 'Hidden-Layer-
1'))
mlp_model.add(Dropout(rate = 0.2, name = 'Dropout-Layer-1'))
mlp_model.add(Dense(1024, activation = 'relu', name = 'Hidden-Layer-
2'))
mlp_model.add(Dropout(rate = 0.2, name = 'Dropout-Layer-2'))
mlp_model.add(Dense(512, activation = 'relu', name = 'Hidden-Layer-
3'))
mlp_model.add(Dropout(rate = 0.2, name = 'Dropout-Layer-3'))
mlp_model.add(Dense(4, activation = 'softmax', name = 'Output-Layer-
1'))
mlp_model.compile(optimizer = 'Adam', loss =
'categorical_crossentropy', metrics = ['accuracy'])
mlp_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Flatten-Layer (Flatten)      (None, 49152)             0
_________________________________________________________________
Hidden-Layer-1 (Dense)       (None, 2048)              100665344
_________________________________________________________________
Dropout-Layer-1 (Dropout)    (None, 2048)              0
_________________________________________________________________
Hidden-Layer-2 (Dense)       (None, 1024)              2098176
_________________________________________________________________
Dropout-Layer-2 (Dropout)    (None, 1024)              0
_________________________________________________________________
Hidden-Layer-3 (Dense)       (None, 512)               524800
_________________________________________________________________
Dropout-Layer-3 (Dropout)    (None, 512)               0
_________________________________________________________________
Output-Layer-1 (Dense)       (None, 4)                 2052
=================================================================
Total params: 103,290,372
Trainable params: 103,290,372
```

```
Non-trainable params: 0
_________________________________________________________________
```

8.1.2 Training and Validation of Multi-Layer Perceptron Based Model

```
with tf.device(gpu_device_location) if gpu_device_location else
tpu_strategy.scope() if tpu_device_location else
tf.device(cpu_device_location):
    mlp_train_history = mlp_model.fit(train_dataset,
                                      batch_size = batch_size,
                                      validation_data =
validation_dataset,
                                      epochs = 100,
                                      callbacks = [early_stopping])

Epoch 1/100
61/61 [==============================] - 847s 14s/step - loss: 4.7656
- accuracy: 0.3957 - val_loss: 1.3696 - val_accuracy: 0.3299
Epoch 2/100
61/61 [==============================] - 77s 1s/step - loss: 1.2743 -
accuracy: 0.4917 - val_loss: 1.1744 - val_accuracy: 0.5629
Epoch 3/100
61/61 [==============================] - 75s 1s/step - loss: 1.1763 -
accuracy: 0.5243 - val_loss: 1.1415 - val_accuracy: 0.5505
Epoch 4/100
61/61 [==============================] - 74s 1s/step - loss: 1.1731 -
accuracy: 0.5232 - val_loss: 1.1290 - val_accuracy: 0.5670
Epoch 5/100
61/61 [==============================] - 74s 1s/step - loss: 1.1487 -
accuracy: 0.5320 - val_loss: 1.1370 - val_accuracy: 0.5423
Epoch 6/100
61/61 [==============================] - 74s 1s/step - loss: 1.1226 -
accuracy: 0.5579 - val_loss: 1.1002 - val_accuracy: 0.5773
Epoch 7/100
61/61 [==============================] - 74s 1s/step - loss: 1.1489 -
accuracy: 0.5403 - val_loss: 1.1865 - val_accuracy: 0.5423
Epoch 8/100
61/61 [==============================] - 73s 1s/step - loss: 1.1077 -
accuracy: 0.5635 - val_loss: 1.1172 - val_accuracy: 0.5691
Epoch 9/100
61/61 [==============================] - 73s 1s/step - loss: 1.1134 -
accuracy: 0.5708 - val_loss: 1.0647 - val_accuracy: 0.5732
Epoch 10/100
61/61 [==============================] - 73s 1s/step - loss: 1.1059 -
accuracy: 0.5697 - val_loss: 1.0703 - val_accuracy: 0.5835
Epoch 11/100
61/61 [==============================] - 73s 1s/step - loss: 1.0625 -
accuracy: 0.5826 - val_loss: 1.0690 - val_accuracy: 0.5835
Epoch 12/100
61/61 [==============================] - 73s 1s/step - loss: 1.0535 -
```

```
accuracy: 0.5821 - val_loss: 1.0487 - val_accuracy: 0.5835
Epoch 13/100
61/61 [==============================] - 74s 1s/step - loss: 1.0763 -
accuracy: 0.5713 - val_loss: 1.0513 - val_accuracy: 0.5918
Epoch 14/100
61/61 [==============================] - 74s 1s/step - loss: 1.0516 -
accuracy: 0.5785 - val_loss: 1.0400 - val_accuracy: 0.5856
Epoch 15/100
61/61 [==============================] - 74s 1s/step - loss: 1.0251 -
accuracy: 0.5919 - val_loss: 1.0699 - val_accuracy: 0.5856
Epoch 16/100
61/61 [==============================] - 74s 1s/step - loss: 1.0348 -
accuracy: 0.5852 - val_loss: 1.0210 - val_accuracy: 0.6041
Epoch 17/100
61/61 [==============================] - 74s 1s/step - loss: 1.0266 -
accuracy: 0.5847 - val_loss: 1.1187 - val_accuracy: 0.6124
Epoch 18/100
61/61 [==============================] - 74s 1s/step - loss: 1.0384 -
accuracy: 0.5888 - val_loss: 1.0726 - val_accuracy: 0.5629
Epoch 19/100
61/61 [==============================] - 73s 1s/step - loss: 1.0218 -
accuracy: 0.5935 - val_loss: 1.0249 - val_accuracy: 0.5918
Epoch 20/100
61/61 [==============================] - 73s 1s/step - loss: 1.0167 -
accuracy: 0.6049 - val_loss: 0.9846 - val_accuracy: 0.6021
Epoch 21/100
61/61 [==============================] - 73s 1s/step - loss: 1.0130 -
accuracy: 0.6012 - val_loss: 0.9933 - val_accuracy: 0.6062
Epoch 22/100
61/61 [==============================] - 73s 1s/step - loss: 0.9902 -
accuracy: 0.6162 - val_loss: 0.9511 - val_accuracy: 0.6289
Epoch 23/100
61/61 [==============================] - 73s 1s/step - loss: 1.0167 -
accuracy: 0.5966 - val_loss: 1.0133 - val_accuracy: 0.5835
Epoch 24/100
61/61 [==============================] - 73s 1s/step - loss: 0.9807 -
accuracy: 0.5992 - val_loss: 1.0058 - val_accuracy: 0.6000
Epoch 25/100
61/61 [==============================] - 73s 1s/step - loss: 1.0206 -
accuracy: 0.5971 - val_loss: 1.0592 - val_accuracy: 0.5711
Epoch 26/100
61/61 [==============================] - 73s 1s/step - loss: 0.9835 -
accuracy: 0.6090 - val_loss: 0.9448 - val_accuracy: 0.6247
Epoch 27/100
61/61 [==============================] - 73s 1s/step - loss: 0.9723 -
accuracy: 0.6178 - val_loss: 0.9680 - val_accuracy: 0.6186
Epoch 28/100
61/61 [==============================] - 74s 1s/step - loss: 0.9614 -
accuracy: 0.6157 - val_loss: 0.9766 - val_accuracy: 0.6165
```

```
Epoch 29/100
61/61 [==============================] - 73s 1s/step - loss: 0.9707 -
accuracy: 0.6198 - val_loss: 0.9779 - val_accuracy: 0.6289
Epoch 30/100
61/61 [==============================] - 73s 1s/step - loss: 1.0039 -
accuracy: 0.6059 - val_loss: 0.9709 - val_accuracy: 0.6082
Epoch 31/100
61/61 [==============================] - 73s 1s/step - loss: 1.0166 -
accuracy: 0.5857 - val_loss: 0.9550 - val_accuracy: 0.6371
Epoch 32/100
61/61 [==============================] - 73s 1s/step - loss: 0.9962 -
accuracy: 0.6002 - val_loss: 0.9459 - val_accuracy: 0.6309
Epoch 33/100
61/61 [==============================] - 73s 1s/step - loss: 0.9699 -
accuracy: 0.6126 - val_loss: 0.9566 - val_accuracy: 0.6268
Epoch 34/100
61/61 [==============================] - 73s 1s/step - loss: 0.9707 -
accuracy: 0.6131 - val_loss: 0.9805 - val_accuracy: 0.6082
Epoch 35/100
61/61 [==============================] - 73s 1s/step - loss: 0.9817 -
accuracy: 0.6105 - val_loss: 0.9733 - val_accuracy: 0.6268
Epoch 36/100
61/61 [==============================] - 74s 1s/step - loss: 0.9715 -
accuracy: 0.6100 - val_loss: 0.9485 - val_accuracy: 0.6392
Epoch 37/100
61/61 [==============================] - 73s 1s/step - loss: 0.9430 -
accuracy: 0.6224 - val_loss: 0.9829 - val_accuracy: 0.6165
Epoch 38/100
61/61 [==============================] - 73s 1s/step - loss: 0.9607 -
accuracy: 0.6173 - val_loss: 0.9563 - val_accuracy: 0.6227
Epoch 39/100
61/61 [==============================] - 73s 1s/step - loss: 0.9476 -
accuracy: 0.6105 - val_loss: 0.9691 - val_accuracy: 0.6351
Epoch 40/100
61/61 [==============================] - 73s 1s/step - loss: 0.9499 -
accuracy: 0.6198 - val_loss: 0.9605 - val_accuracy: 0.6371
Epoch 41/100
61/61 [==============================] - 73s 1s/step - loss: 0.9481 -
accuracy: 0.6147 - val_loss: 0.9770 - val_accuracy: 0.6392
Epoch 42/100
61/61 [==============================] - 74s 1s/step - loss: 0.9364 -
accuracy: 0.6162 - val_loss: 1.0055 - val_accuracy: 0.6392
Epoch 43/100
61/61 [==============================] - 73s 1s/step - loss: 0.9902 -
accuracy: 0.6043 - val_loss: 0.9579 - val_accuracy: 0.6309
Epoch 44/100
61/61 [==============================] - 74s 1s/step - loss: 0.9823 -
accuracy: 0.6142 - val_loss: 1.0254 - val_accuracy: 0.6041
Epoch 45/100
```

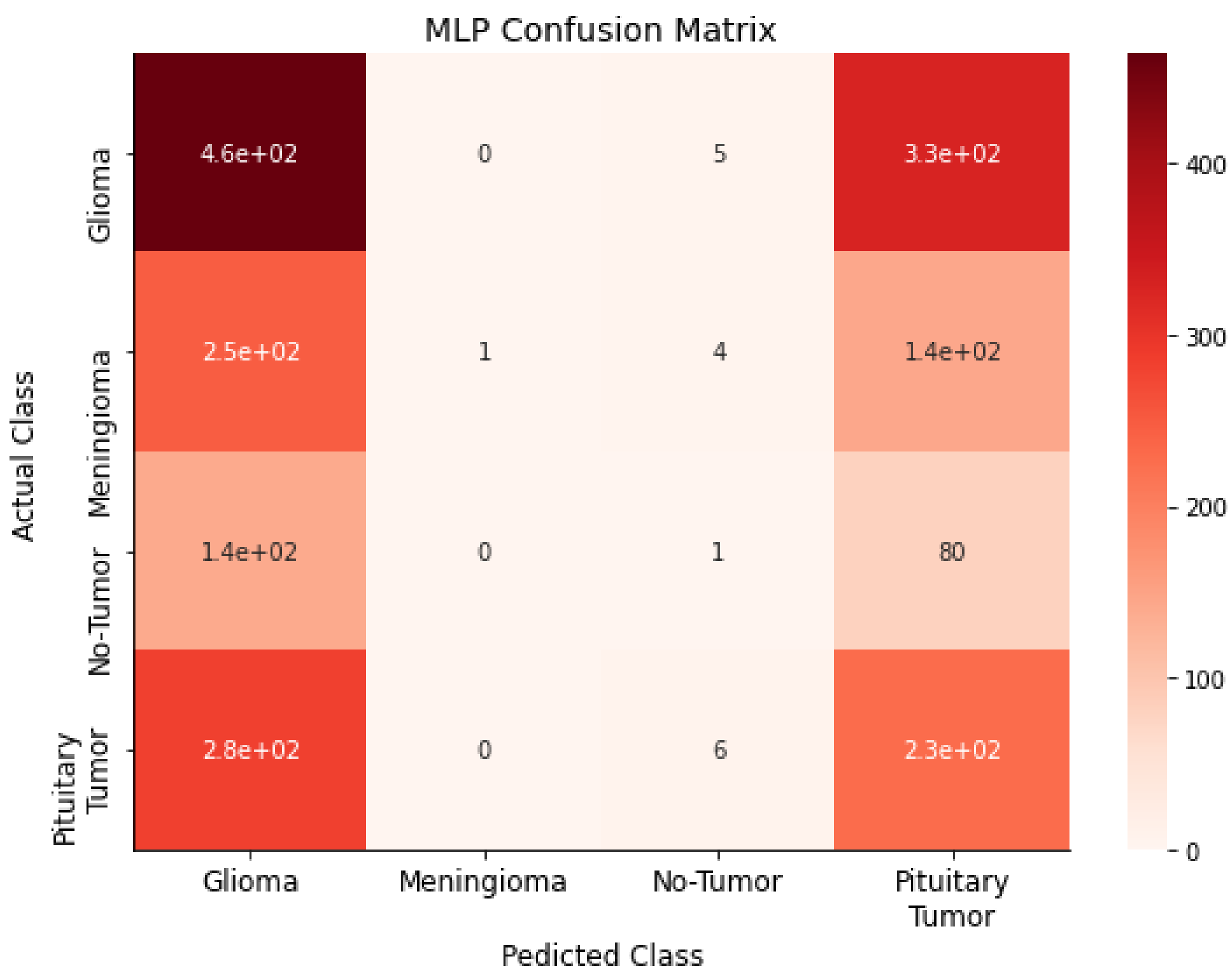
```
61/61 [==============================] - 74s 1s/step - loss: 0.9551 -
accuracy: 0.6064 - val_loss: 0.9354 - val_accuracy: 0.6474
Epoch 46/100
61/61 [==============================] - 74s 1s/step - loss: 0.9600 -
accuracy: 0.6147 - val_loss: 0.9321 - val_accuracy: 0.6474
Epoch 47/100
61/61 [==============================] - 73s 1s/step - loss: 0.9266 -
accuracy: 0.6229 - val_loss: 0.9412 - val_accuracy: 0.6330
Epoch 48/100
61/61 [==============================] - 74s 1s/step - loss: 0.9405 -
accuracy: 0.6219 - val_loss: 0.9390 - val_accuracy: 0.6515
Epoch 49/100
61/61 [==============================] - 74s 1s/step - loss: 0.9551 -
accuracy: 0.6214 - val_loss: 0.9330 - val_accuracy: 0.6371
Epoch 50/100
61/61 [==============================] - 73s 1s/step - loss: 0.9704 -
accuracy: 0.6157 - val_loss: 0.9832 - val_accuracy: 0.6041
Epoch 51/100
61/61 [==============================] - 73s 1s/step - loss: 0.9604 -
accuracy: 0.6204 - val_loss: 0.9360 - val_accuracy: 0.6289
Epoch 52/100
61/61 [==============================] - 73s 1s/step - loss: 0.9545 -
accuracy: 0.6219 - val_loss: 0.9978 - val_accuracy: 0.6206
Epoch 53/100
61/61 [==============================] - 73s 1s/step - loss: 0.9547 -
accuracy: 0.6260 - val_loss: 0.9343 - val_accuracy: 0.6392
Epoch 54/100
61/61 [==============================] - 73s 1s/step - loss: 0.9417 -
accuracy: 0.6229 - val_loss: 0.9262 - val_accuracy: 0.6371
Epoch 55/100
61/61 [==============================] - 73s 1s/step - loss: 0.9335 -
accuracy: 0.6281 - val_loss: 0.9395 - val_accuracy: 0.6206
Epoch 56/100
61/61 [==============================] - 73s 1s/step - loss: 0.9317 -
accuracy: 0.6240 - val_loss: 0.9245 - val_accuracy: 0.6392
Epoch 57/100
61/61 [==============================] - 73s 1s/step - loss: 0.9670 -
accuracy: 0.6142 - val_loss: 0.9657 - val_accuracy: 0.6371
Epoch 58/100
61/61 [==============================] - 73s 1s/step - loss: 0.9434 -
accuracy: 0.6224 - val_loss: 1.0117 - val_accuracy: 0.6124
```

8.1.3 Multi-Layer Perceptron Based Model Training Process Statistics

```
training_process_viz(pd.DataFrame(mlp_train_history.history),
                     plot_title = 'Multilayer Perceptron Training
Statistics')
```

8.1.4 Confusion Matrix for Multi-Layer Perceptron Based Model

```
confusion_matrix_viz(mlp_model, train_dataset, plot_title = "MLP
Confusion Matrix")
```



```
mlp_report_df = generate_report(mlp_model,
                                test_dataset = test_dataset,
                                row_indexes = ("Multi-Layer-Perceptron
Model",))
mlp_report_df
```

```
33/33 [==============================] - 33s 991ms/step - loss: 0.9263
- accuracy: 0.6243
```

```
                                  MAE       MSE  ...  Accuracy  F1-
Score
Multi-Layer-Perceptron Model  1.39499  3.533719  ...  0.624277
0.368979

[1 rows x 6 columns]
```

8.2 AlexNet CNN

8.2.1 Develoment of AlexNet CNN Model

```
alexnet_cnn = Sequential()
alexnet_cnn.add(Conv2D(96, kernel_size = 11, strides = 4, activation =
'relu', input_shape = (image_size, image_size, 3), name = 'Conv2D-1'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-1'))
alexnet_cnn.add(MaxPool2D(pool_size = 3, strides = 2, name = 'Max-
Pooling-1'))
alexnet_cnn.add(Conv2D(256, kernel_size = 5, padding = 'same',
activation = 'relu', name = 'Conv2D-2'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-2'))
alexnet_cnn.add(MaxPool2D(pool_size = 3, strides = 2, name = 'Max-
Pooling-2'))
alexnet_cnn.add(Conv2D(384, kernel_size = 3, padding = 'same',
activation = 'relu', name = 'Conv2D-3'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-3'))
alexnet_cnn.add(Conv2D(384, kernel_size = 3, padding = 'same',
activation = 'relu', name = 'Conv2D-4'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-4'))
alexnet_cnn.add(Conv2D(256, kernel_size = 3, padding = 'same',
activation = 'relu', name = 'Conv2D-5'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-5'))
alexnet_cnn.add(MaxPool2D(pool_size = 3, strides = 2, name = 'Max-
Pooling-3'))
alexnet_cnn.add(Flatten(name = 'Flatten-Layer-1'))
alexnet_cnn.add(Dense(128, activation = 'relu', name = 'Hidden-Layer-
1'))
alexnet_cnn.add(Dropout(rate = 0.5, name = 'Dropout-Layer-1'))
alexnet_cnn.add(Dense(64, activation = 'relu', name = 'Hidden-Layer-
2'))
alexnet_cnn.add(Dropout(rate = 0.5, name = 'Dropout-Layer-2'))
alexnet_cnn.add(Dense(4, activation = 'softmax', name = 'Output-
```

```
Layer'))
alexnet_cnn.compile(optimizer = 'Adam', loss =
'categorical_crossentropy', metrics = ['accuracy'])
alexnet_cnn.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Conv2D-1 (Conv2D)            (None, 30, 30, 96)        34944
_________________________________________________________________
Batch-Normalization-1 (Batch (None, 30, 30, 96)        384
_________________________________________________________________
Max-Pooling-1 (MaxPooling2D) (None, 14, 14, 96)        0
_________________________________________________________________
Conv2D-2 (Conv2D)            (None, 14, 14, 256)       614656
_________________________________________________________________
Batch-Normalization-2 (Batch (None, 14, 14, 256)       1024
_________________________________________________________________
Max-Pooling-2 (MaxPooling2D) (None, 6, 6, 256)         0
_________________________________________________________________
Conv2D-3 (Conv2D)            (None, 6, 6, 384)         885120
_________________________________________________________________
Batch-Normalization-3 (Batch (None, 6, 6, 384)         1536
_________________________________________________________________
Conv2D-4 (Conv2D)            (None, 6, 6, 384)         1327488
_________________________________________________________________
Batch-Normalization-4 (Batch (None, 6, 6, 384)         1536
_________________________________________________________________
Conv2D-5 (Conv2D)            (None, 6, 6, 256)         884992
_________________________________________________________________
Batch-Normalization-5 (Batch (None, 6, 6, 256)         1024
_________________________________________________________________
Max-Pooling-3 (MaxPooling2D) (None, 2, 2, 256)         0
_________________________________________________________________
Flatten-Layer-1 (Flatten)    (None, 1024)              0
_________________________________________________________________
Hidden-Layer-1 (Dense)       (None, 128)               131200
_________________________________________________________________
Dropout-Layer-1 (Dropout)    (None, 128)               0
_________________________________________________________________
Hidden-Layer-2 (Dense)       (None, 64)                8256
_________________________________________________________________
Dropout-Layer-2 (Dropout)    (None, 64)                0
_________________________________________________________________
Output-Layer (Dense)         (None, 4)                 260
=================================================================
Total params: 3,892,420
Trainable params: 3,889,668
```

```
Non-trainable params: 2,752
_________________________________________________________________
```

8.2.2 Training and Validation of AlexNet CNN Model

```
with tf.device(gpu_device_location) if gpu_device_location else
tpu_strategy.scope() if tpu_device_location else
tf.device(cpu_device_location):
    alexnet_train_history = alexnet_cnn.fit(train_dataset,
                                            batch_size = batch_size,
                                            validation_data =
validation_dataset,
                                            epochs = 100,
                                            callbacks =
[early_stopping, alexnet_cp_callback])

Epoch 1/100
61/61 [==============================] - 106s 1s/step - loss: 1.9368 -
accuracy: 0.3745 - val_loss: 1.3511 - val_accuracy: 0.3361

Epoch 00001: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 2/100
61/61 [==============================] - 75s 1s/step - loss: 1.3039 -
accuracy: 0.4236 - val_loss: 1.4838 - val_accuracy: 0.2701

Epoch 00002: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 3/100
61/61 [==============================] - 75s 1s/step - loss: 1.2819 -
accuracy: 0.4396 - val_loss: 1.4569 - val_accuracy: 0.2825

Epoch 00003: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 4/100
61/61 [==============================] - 75s 1s/step - loss: 1.2649 -
accuracy: 0.4824 - val_loss: 1.2596 - val_accuracy: 0.4433

Epoch 00004: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 5/100
61/61 [==============================] - 75s 1s/step - loss: 1.1811 -
accuracy: 0.5269 - val_loss: 1.9028 - val_accuracy: 0.4124

Epoch 00005: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
```

```
CNN
Epoch 6/100
61/61 [==============================] - 75s 1s/step - loss: 1.1224 -
accuracy: 0.5532 - val_loss: 1.1000 - val_accuracy: 0.5464

Epoch 00006: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 7/100
61/61 [==============================] - 75s 1s/step - loss: 1.0914 -
accuracy: 0.5656 - val_loss: 1.3219 - val_accuracy: 0.5093

Epoch 00007: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 8/100
61/61 [==============================] - 74s 1s/step - loss: 1.0605 -
accuracy: 0.5816 - val_loss: 1.0640 - val_accuracy: 0.5711

Epoch 00008: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 9/100
61/61 [==============================] - 75s 1s/step - loss: 1.0418 -
accuracy: 0.5925 - val_loss: 1.0312 - val_accuracy: 0.6041

Epoch 00009: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 10/100
61/61 [==============================] - 74s 1s/step - loss: 0.9587 -
accuracy: 0.6095 - val_loss: 1.0401 - val_accuracy: 0.5711

Epoch 00010: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 11/100
61/61 [==============================] - 74s 1s/step - loss: 0.9697 -
accuracy: 0.5992 - val_loss: 1.3941 - val_accuracy: 0.4969

Epoch 00011: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 12/100
61/61 [==============================] - 74s 1s/step - loss: 0.9032 -
accuracy: 0.6426 - val_loss: 1.0185 - val_accuracy: 0.5773

Epoch 00012: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
```

```
Epoch 13/100
61/61 [==============================] - 74s 1s/step - loss: 0.8973 -
accuracy: 0.6426 - val_loss: 1.2468 - val_accuracy: 0.5546

Epoch 00013: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 14/100
61/61 [==============================] - 74s 1s/step - loss: 0.8586 -
accuracy: 0.6426 - val_loss: 0.8579 - val_accuracy: 0.6639

Epoch 00014: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 15/100
61/61 [==============================] - 74s 1s/step - loss: 0.8298 -
accuracy: 0.6668 - val_loss: 1.0546 - val_accuracy: 0.6206

Epoch 00015: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 16/100
61/61 [==============================] - 74s 1s/step - loss: 0.8412 -
accuracy: 0.6606 - val_loss: 0.8214 - val_accuracy: 0.6825

Epoch 00016: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 17/100
61/61 [==============================] - 74s 1s/step - loss: 0.8241 -
accuracy: 0.6606 - val_loss: 0.8492 - val_accuracy: 0.6825

Epoch 00017: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 18/100
61/61 [==============================] - 74s 1s/step - loss: 0.7722 -
accuracy: 0.6834 - val_loss: 1.1481 - val_accuracy: 0.5320

Epoch 00018: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 19/100
61/61 [==============================] - 74s 1s/step - loss: 0.8068 -
accuracy: 0.6736 - val_loss: 0.8517 - val_accuracy: 0.6660

Epoch 00019: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 20/100
```

```
61/61 [==============================] - 74s 1s/step - loss: 0.7517 -
accuracy: 0.6942 - val_loss: 1.0671 - val_accuracy: 0.5856

Epoch 00020: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 21/100
61/61 [==============================] - 74s 1s/step - loss: 0.7691 -
accuracy: 0.6854 - val_loss: 0.7761 - val_accuracy: 0.6825

Epoch 00021: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 22/100
61/61 [==============================] - 74s 1s/step - loss: 0.7211 -
accuracy: 0.7030 - val_loss: 0.7683 - val_accuracy: 0.6845

Epoch 00022: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 23/100
61/61 [==============================] - 74s 1s/step - loss: 0.7188 -
accuracy: 0.7113 - val_loss: 0.8285 - val_accuracy: 0.6412

Epoch 00023: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 24/100
61/61 [==============================] - 74s 1s/step - loss: 0.6995 -
accuracy: 0.7102 - val_loss: 0.9983 - val_accuracy: 0.6062

Epoch 00024: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 25/100
61/61 [==============================] - 74s 1s/step - loss: 0.6989 -
accuracy: 0.7118 - val_loss: 0.7648 - val_accuracy: 0.6907

Epoch 00025: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 26/100
61/61 [==============================] - 74s 1s/step - loss: 0.6745 -
accuracy: 0.7082 - val_loss: 0.7971 - val_accuracy: 0.6701

Epoch 00026: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 27/100
61/61 [==============================] - 74s 1s/step - loss: 0.6660 -
```

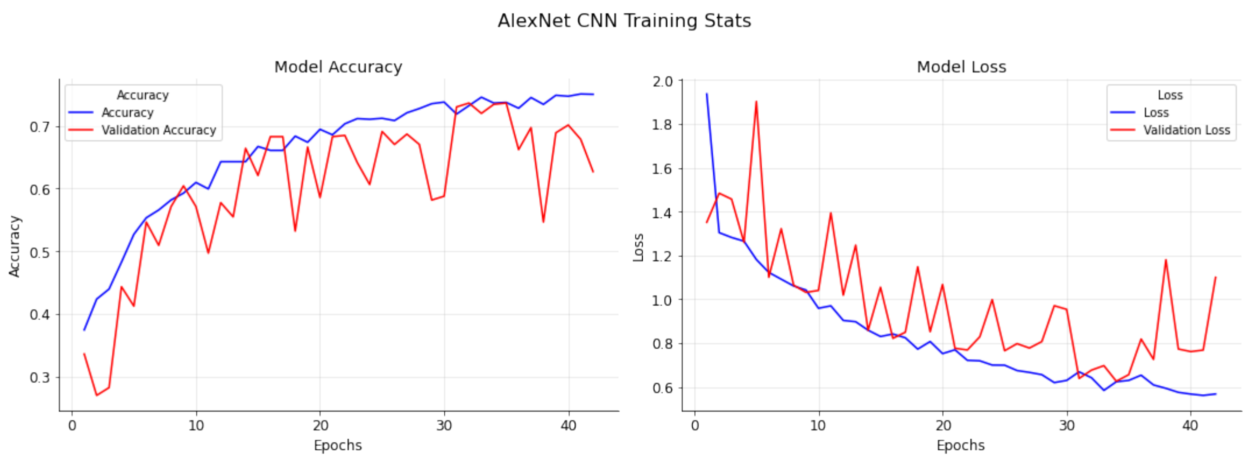
```
accuracy: 0.7206 - val_loss: 0.7770 - val_accuracy: 0.6866

Epoch 00027: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 28/100
61/61 [==============================] - 73s 1s/step - loss: 0.6556 -
accuracy: 0.7273 - val_loss: 0.8068 - val_accuracy: 0.6701

Epoch 00028: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 29/100
61/61 [==============================] - 74s 1s/step - loss: 0.6195 -
accuracy: 0.7350 - val_loss: 0.9703 - val_accuracy: 0.5814

Epoch 00029: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 30/100
61/61 [==============================] - 74s 1s/step - loss: 0.6294 -
accuracy: 0.7376 - val_loss: 0.9537 - val_accuracy: 0.5876

Epoch 00030: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 31/100
61/61 [==============================] - 74s 1s/step - loss: 0.6685 -
accuracy: 0.7185 - val_loss: 0.6383 - val_accuracy: 0.7299

Epoch 00031: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 32/100
61/61 [==============================] - 74s 1s/step - loss: 0.6416 -
accuracy: 0.7319 - val_loss: 0.6763 - val_accuracy: 0.7361

Epoch 00032: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 33/100
61/61 [==============================] - 74s 1s/step - loss: 0.5837 -
accuracy: 0.7454 - val_loss: 0.6968 - val_accuracy: 0.7196

Epoch 00033: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 34/100
61/61 [==============================] - 74s 1s/step - loss: 0.6233 -
accuracy: 0.7361 - val_loss: 0.6255 - val_accuracy: 0.7340
```

```
Epoch 00034: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 35/100
61/61 [==============================] - 74s 1s/step - loss: 0.6294 -
accuracy: 0.7371 - val_loss: 0.6555 - val_accuracy: 0.7361

Epoch 00035: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 36/100
61/61 [==============================] - 74s 1s/step - loss: 0.6532 -
accuracy: 0.7278 - val_loss: 0.8182 - val_accuracy: 0.6619

Epoch 00036: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 37/100
61/61 [==============================] - 74s 1s/step - loss: 0.6086 -
accuracy: 0.7448 - val_loss: 0.7252 - val_accuracy: 0.6969

Epoch 00037: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 38/100
61/61 [==============================] - 74s 1s/step - loss: 0.5932 -
accuracy: 0.7340 - val_loss: 1.1803 - val_accuracy: 0.5464

Epoch 00038: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 39/100
61/61 [==============================] - 74s 1s/step - loss: 0.5749 -
accuracy: 0.7485 - val_loss: 0.7726 - val_accuracy: 0.6887

Epoch 00039: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 40/100
61/61 [==============================] - 74s 1s/step - loss: 0.5670 -
accuracy: 0.7469 - val_loss: 0.7610 - val_accuracy: 0.7010

Epoch 00040: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 41/100
61/61 [==============================] - 74s 1s/step - loss: 0.5610 -
accuracy: 0.7505 - val_loss: 0.7677 - val_accuracy: 0.6784
```

```
Epoch 00041: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
Epoch 42/100
61/61 [==============================] - 74s 1s/step - loss: 0.5674 -
accuracy: 0.7500 - val_loss: 1.0997 - val_accuracy: 0.6268

Epoch 00042: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/AlexNet-
CNN
```

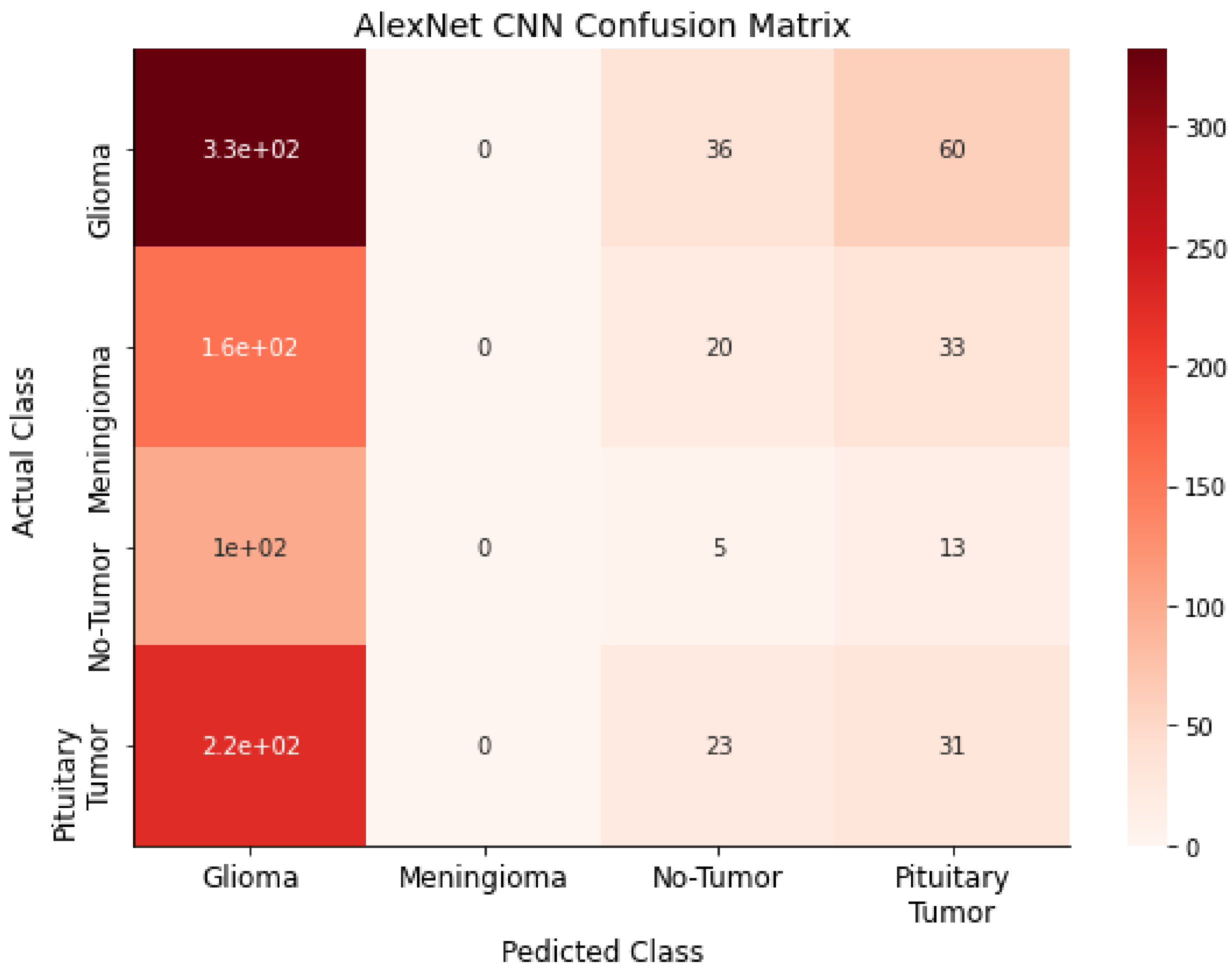
8.2.3 AlexNet CNN Model Training Process Statistics

```
training_process_viz(pd.DataFrame(alexnet_train_history.history),
plot_title = 'AlexNet CNN Training Stats')
```



8.2.4 Confusion Matrix for AlexNet CNN Model

```
with tf.device(gpu_device_location) if gpu_device_location else
tpu_strategy.scope() if tpu_device_name else
tf.device(cpu_device_location):
    confusion_matrix_viz(alexnet_cnn,
                         test_dataset,
                         plot_title = "AlexNet CNN Confusion Matrix")
```




```
alexnet_report_df = generate_report(alexnet_cnn, test_dataset =
test_dataset, row_indexes = ['AlexNet CNN'])
alexnet_report_df

33/33 [==============================] - 33s 988ms/step - loss: 1.1357
- accuracy: 0.6079

                  MAE       MSE      RMSE      Loss  Accuracy  F1-
Score
AlexNet CNN  1.301541  3.205202  1.790308  1.135692    0.6079
0.382466
```

8.3 Inception V3

8.3.1 Developement of InceptionV3

```
inception_v3_model = InceptionV3(include_top = False,
                                 input_shape = (image_size,
image_size, 3),
```

```
                                 pooling = 'avg')
inception_v3_model.trainable = False
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/inception_v3/
inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5
87916544/87910968 [==============================] - 1s 0us/step
```

```
inception_cnn_model = Sequential()
inception_cnn_model.add(inception_v3_model)
inception_cnn_model.add(Flatten())
inception_cnn_model.add(Dense(1024, activation = 'relu', name =
'Hidden-Layer-1'))
inception_cnn_model.add(Dense(4, activation = 'softmax', name =
'Output-Layer'))
inception_cnn_model.compile(optimizer = 'Adam', loss =
'categorical_crossentropy', metrics = ['accuracy'])
inception_cnn_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inception_v3 (Functional)    (None, 2048)              21802784
_________________________________________________________________
flatten (Flatten)            (None, 2048)              0
_________________________________________________________________
Hidden-Layer-1 (Dense)       (None, 1024)              2098176
_________________________________________________________________
Output-Layer (Dense)         (None, 4)                 4100
=================================================================
Total params: 23,905,060
Trainable params: 2,102,276
Non-trainable params: 21,802,784
_________________________________________________________________
```

8.3.2 Training and Validation of InceptionV3 Model

```
with tf.device(gpu_device_location) if gpu_device_location else
tpu_strategy.scope() if tpu_device_location else
tf.device(cpu_device_location):
    inception_model_train_history =
inception_cnn_model.fit(train_dataset,
                                                            batch_size
= batch_size,

validation_data = validation_dataset,
                                                            epochs =
100,
```

```
                                                                 callbacks
= [early_stopping, inceptionv3_cp_callback])

Epoch 1/100
61/61 [==============================] - 83s 1s/step - loss: 1.8779 -
accuracy: 0.6012 - val_loss: 0.7379 - val_accuracy: 0.7113

Epoch 00001: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 2/100
61/61 [==============================] - 76s 1s/step - loss: 0.6863 -
accuracy: 0.7335 - val_loss: 0.6218 - val_accuracy: 0.7979

Epoch 00002: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 3/100
61/61 [==============================] - 76s 1s/step - loss: 0.6144 -
accuracy: 0.7670 - val_loss: 0.6042 - val_accuracy: 0.7835

Epoch 00003: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 4/100
61/61 [==============================] - 76s 1s/step - loss: 0.5593 -
accuracy: 0.7774 - val_loss: 0.8480 - val_accuracy: 0.6536

Epoch 00004: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 5/100
61/61 [==============================] - 76s 1s/step - loss: 0.5345 -
accuracy: 0.7887 - val_loss: 0.5721 - val_accuracy: 0.7732

Epoch 00005: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 6/100
61/61 [==============================] - 75s 1s/step - loss: 0.4957 -
accuracy: 0.8135 - val_loss: 0.6748 - val_accuracy: 0.7485

Epoch 00006: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 7/100
61/61 [==============================] - 75s 1s/step - loss: 0.4660 -
accuracy: 0.8156 - val_loss: 0.5046 - val_accuracy: 0.8000

Epoch 00007: saving model to
```

```
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 8/100
61/61 [==============================] - 75s 1s/step - loss: 0.4784 -
accuracy: 0.8171 - val_loss: 0.6136 - val_accuracy: 0.7649

Epoch 00008: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 9/100
61/61 [==============================] - 75s 1s/step - loss: 0.4769 -
accuracy: 0.8032 - val_loss: 0.5283 - val_accuracy: 0.7876

Epoch 00009: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 10/100
61/61 [==============================] - 75s 1s/step - loss: 0.4529 -
accuracy: 0.8223 - val_loss: 0.5484 - val_accuracy: 0.8000

Epoch 00010: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 11/100
61/61 [==============================] - 75s 1s/step - loss: 0.4472 -
accuracy: 0.8275 - val_loss: 0.4995 - val_accuracy: 0.8062

Epoch 00011: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 12/100
61/61 [==============================] - 75s 1s/step - loss: 0.3815 -
accuracy: 0.8456 - val_loss: 0.5364 - val_accuracy: 0.7979

Epoch 00012: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 13/100
61/61 [==============================] - 75s 1s/step - loss: 0.4216 -
accuracy: 0.8388 - val_loss: 0.5230 - val_accuracy: 0.7835

Epoch 00013: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 14/100
61/61 [==============================] - 75s 1s/step - loss: 0.4312 -
accuracy: 0.8285 - val_loss: 0.5177 - val_accuracy: 0.7979

Epoch 00014: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
```

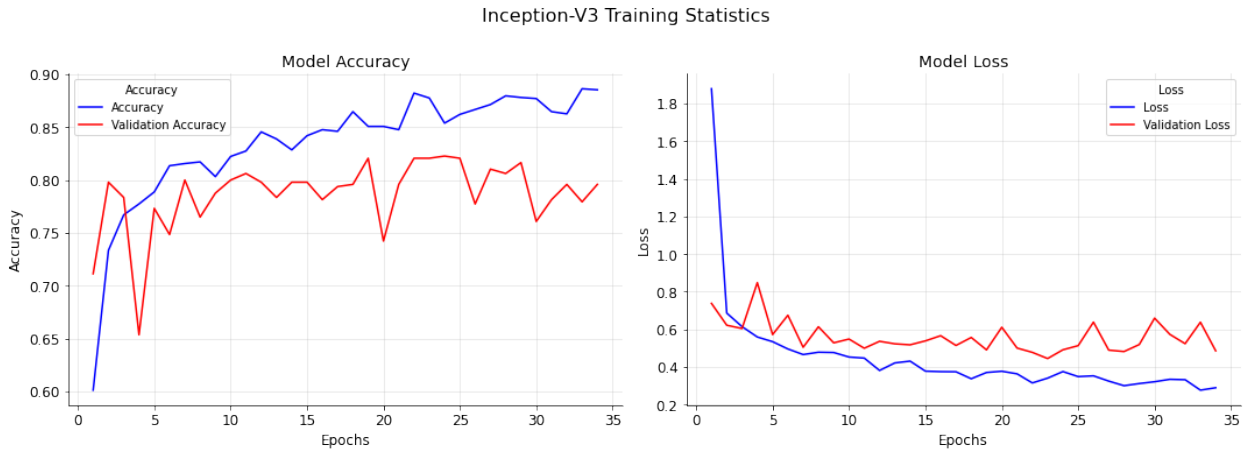
```
nV3
Epoch 15/100
61/61 [==============================] - 75s 1s/step - loss: 0.3779 -
accuracy: 0.8419 - val_loss: 0.5387 - val_accuracy: 0.7979

Epoch 00015: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 16/100
61/61 [==============================] - 74s 1s/step - loss: 0.3753 -
accuracy: 0.8476 - val_loss: 0.5662 - val_accuracy: 0.7814

Epoch 00016: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 17/100
61/61 [==============================] - 75s 1s/step - loss: 0.3746 -
accuracy: 0.8461 - val_loss: 0.5143 - val_accuracy: 0.7938

Epoch 00017: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 18/100
61/61 [==============================] - 74s 1s/step - loss: 0.3375 -
accuracy: 0.8647 - val_loss: 0.5568 - val_accuracy: 0.7959

Epoch 00018: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 19/100
61/61 [==============================] - 74s 1s/step - loss: 0.3707 -
accuracy: 0.8507 - val_loss: 0.4909 - val_accuracy: 0.8206

Epoch 00019: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 20/100
61/61 [==============================] - 75s 1s/step - loss: 0.3774 -
accuracy: 0.8507 - val_loss: 0.6110 - val_accuracy: 0.7423

Epoch 00020: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 21/100
61/61 [==============================] - 75s 1s/step - loss: 0.3636 -
accuracy: 0.8476 - val_loss: 0.5006 - val_accuracy: 0.7959

Epoch 00021: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
```

```
Epoch 22/100
61/61 [==============================] - 74s 1s/step - loss: 0.3153 - accuracy: 0.8822 - val_loss: 0.4776 - val_accuracy: 0.8206

Epoch 00022: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 23/100
61/61 [==============================] - 75s 1s/step - loss: 0.3407 - accuracy: 0.8776 - val_loss: 0.4448 - val_accuracy: 0.8206

Epoch 00023: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 24/100
61/61 [==============================] - 75s 1s/step - loss: 0.3756 - accuracy: 0.8538 - val_loss: 0.4913 - val_accuracy: 0.8227

Epoch 00024: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 25/100
61/61 [==============================] - 75s 1s/step - loss: 0.3489 - accuracy: 0.8621 - val_loss: 0.5133 - val_accuracy: 0.8206

Epoch 00025: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 26/100
61/61 [==============================] - 74s 1s/step - loss: 0.3531 - accuracy: 0.8667 - val_loss: 0.6384 - val_accuracy: 0.7773

Epoch 00026: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 27/100
61/61 [==============================] - 75s 1s/step - loss: 0.3250 - accuracy: 0.8714 - val_loss: 0.4896 - val_accuracy: 0.8103

Epoch 00027: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 28/100
61/61 [==============================] - 75s 1s/step - loss: 0.3006 - accuracy: 0.8796 - val_loss: 0.4820 - val_accuracy: 0.8062

Epoch 00028: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/InceptionV3
Epoch 29/100
```

```
61/61 [==============================] - 75s 1s/step - loss: 0.3121 -
accuracy: 0.8781 - val_loss: 0.5193 - val_accuracy: 0.8165

Epoch 00029: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 30/100
61/61 [==============================] - 75s 1s/step - loss: 0.3217 -
accuracy: 0.8771 - val_loss: 0.6595 - val_accuracy: 0.7608

Epoch 00030: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 31/100
61/61 [==============================] - 75s 1s/step - loss: 0.3345 -
accuracy: 0.8647 - val_loss: 0.5732 - val_accuracy: 0.7814

Epoch 00031: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 32/100
61/61 [==============================] - 75s 1s/step - loss: 0.3324 -
accuracy: 0.8626 - val_loss: 0.5237 - val_accuracy: 0.7959

Epoch 00032: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 33/100
61/61 [==============================] - 75s 1s/step - loss: 0.2770 -
accuracy: 0.8864 - val_loss: 0.6379 - val_accuracy: 0.7794

Epoch 00033: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
Epoch 34/100
61/61 [==============================] - 75s 1s/step - loss: 0.2898 -
accuracy: 0.8853 - val_loss: 0.4858 - val_accuracy: 0.7959

Epoch 00034: saving model to
gdrive/MyDrive/Deep_Learning_Course_Project/Model-Checkpoints/Inceptio
nV3
```

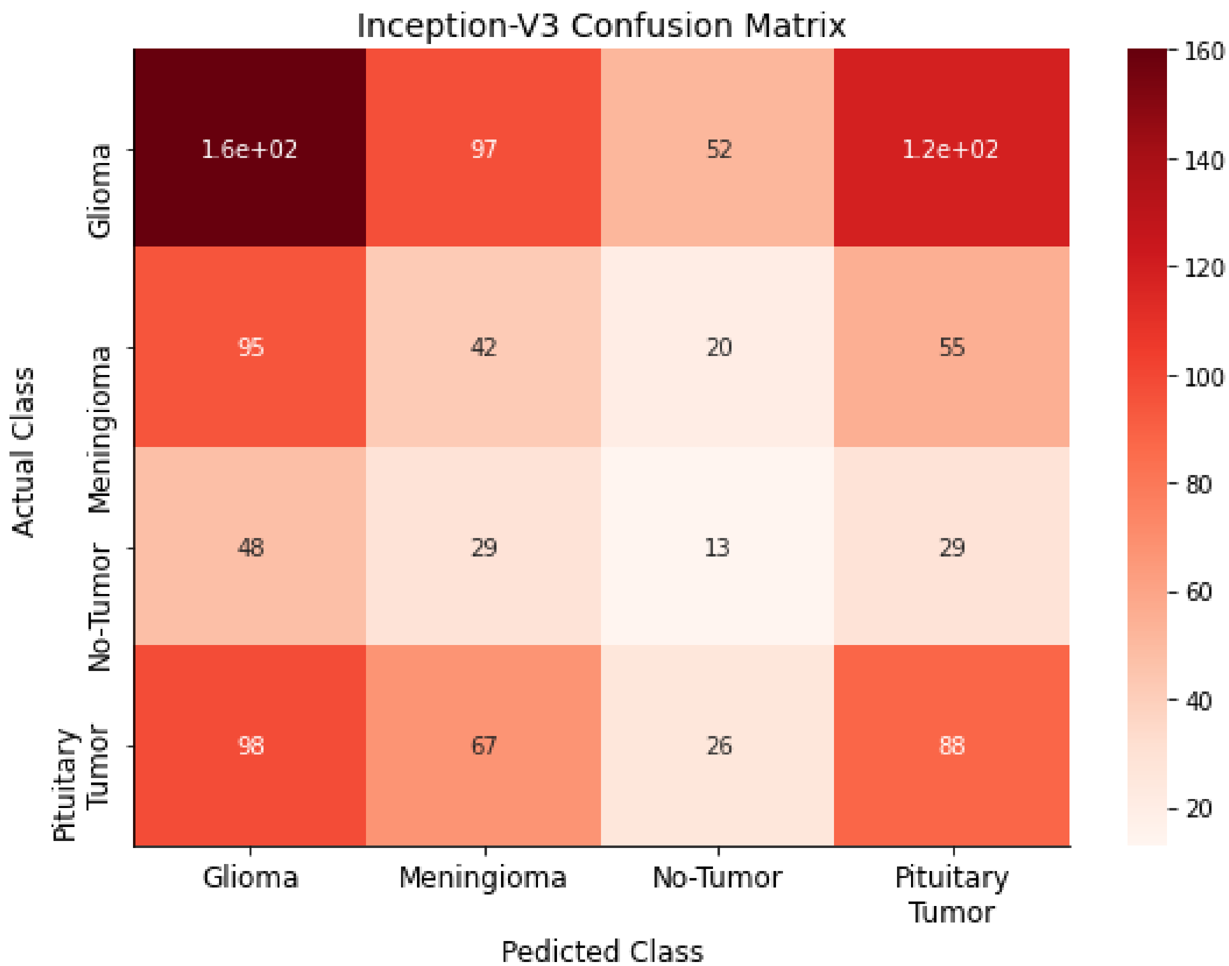
8.3.3 InceptionV3 Model Training Process Statistics

```
training_process_viz(pd.DataFrame(inception_model_train_history.histor
y),
                     plot_title = 'Inception-V3 Training Statistics')
```



8.3.4 Confusion Matrix for InceptionV3 Model

```
with tf.device(gpu_device_location) if gpu_device_location else
tpu_strategy.scope() if tpu_device_location else
tf.device(cpu_device_name):
    confusion_matrix_viz(inception_cnn_model,
                         test_dataset,
                         plot_title = "Inception-V3 Confusion Matrix")
```




```
inceptionv3_report_df = generate_report(inception_cnn_model,
test_dataset = test_dataset, row_indexes = ['InceptionV3'])
inceptionv3_report_df

33/33 [==============================] - 32s 962ms/step - loss: 0.4522
- accuracy: 0.8256

                  MAE       MSE      RMSE      Loss  Accuracy  F1-Score
InceptionV3  1.365125  3.101156  1.76101  0.452249  0.825626    0.2842
```

9. Conclusions

- The **pre-trained (imagenet) InceptionV3** model has performed the best among Multi-Layer perceptron and AlexNet CNN models with an accuracy of 82.57% (Refer the following table).

```
final_report_df = pd.concat([mlp_report_df, alexnet_report_df,
inceptionv3_report_df])
final_report_df
```

```
                                  MAE       MSE  ...  Accuracy  F1-
Score
Multi-Layer-Perceptron Model  1.394990  3.533719  ...  0.624277
0.368979
AlexNet CNN                   1.301541  3.205202  ...  0.607900
0.382466
InceptionV3                   1.365125  3.101156  ...  0.825626
0.284200

[3 rows x 6 columns]
```

10. Future Works

- To incorporate a Data Augmentation pipeline to efficiently generate various different variants of the iamges to make the model more roboust.
- Training process will be migrated to TPUs (Tensor Processing Units) by representing the data in TFRecord format for significant reduction in training time.
- Implementation of R-CNN to not only detect a image which has a tumor in it but to also label the location of the tumor in the image.